2021 SISBID Clustering Lab

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Data set - Author Data.

This data set consists of word counts from chapters written by four British authors.
This lab will put together concepts from both dimension reduction and clustering.
There are ultimately 3 goals to this lab:
* Correctly cluster author texts in an unsupervised manner.
* Determine which words are responsible for correctly separating the author texts.
* Visualize the author texts, words and the results of your analysis.

1. Problem 1 - Visualization

- Problem 1a - We wish to plot the author texts as well as the words via a 2D scatterplot. Which method would be best to use? Why?
- Problem 1b - Apply PCA to visualize the author texts. Explain the results.
- Problem 1c - Apply MDS to visualize the author texts. Interpret the results.
- Problem 1d - Can you use MDS to help determine which distance is appropriate for this data? Which one is best and why?
- Problem 1e - Apply MDS with your chosen distance to visualize the words. Interpret the results.

2. Problem 2 - K-means

- Problem 2a - Apply K-means with K=4 to this data.
- Problem 2b - How well does K-mean do at separating the authors?
- Problem 2c - Is K-means an appropriate clustering algorithm for this data? Why or Why not?

3. Problem 3 - Hierarchical Clustering

- Problem 3a - Apply hierarchical clustering to this data set.
- Problem 3b - Which distance is best to use? Why?
- Problem 3c - Which linkage is best to use? Why?
- Problem 3d - Do any linkages perform particularly poorly? Explain this result.
- Problem 3e - Visualize your hierarchical clustering results.

4. Problem 4 - Biclustering

- Problem 4a - Apply the cluster heatmap method to visualize this data. Which distance and linkage functions did you use?
- Problem 4b - Interpret the cluster heatmap. Which words are important for distinguishing author texts?

5. Problem 5 - NMF

- Problem 5a - Apply NMF with K = 4 and use W to assign cluster labels to each observation.
- Problem 5b - How well does NMF perform? Interpret and explain this result.

- Problem 5c - Can you use the NMF to determine which words are important for distinguishing author texts? How? What did you find?

6. Problem 6 - Wrap-up

- Problem 6a - Overall, which method is the best at clustering the author texts? Why is this the case?
- Problem 6b - Which words are key for distinguishing the author texts? How did you determine these?
- Problem 6c - Overall, which is the best method for providing a visual summary of the data?

R scripts to help out with the Clustering Lab Don't peek at this if you want to practice coding on your own!!

Load packages

```
library(NMF)
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 3.6.2
```

```
library(umap)
```

```
## Warning: package 'umap' was built under R version 3.6.2
```

Load dataset: Author data

```
load("UnsupL_SISBID_2021.Rdata")
# understand the data a bit
dim(author)
```

```
## [1] 841  70
```

```
colnames(author)
```

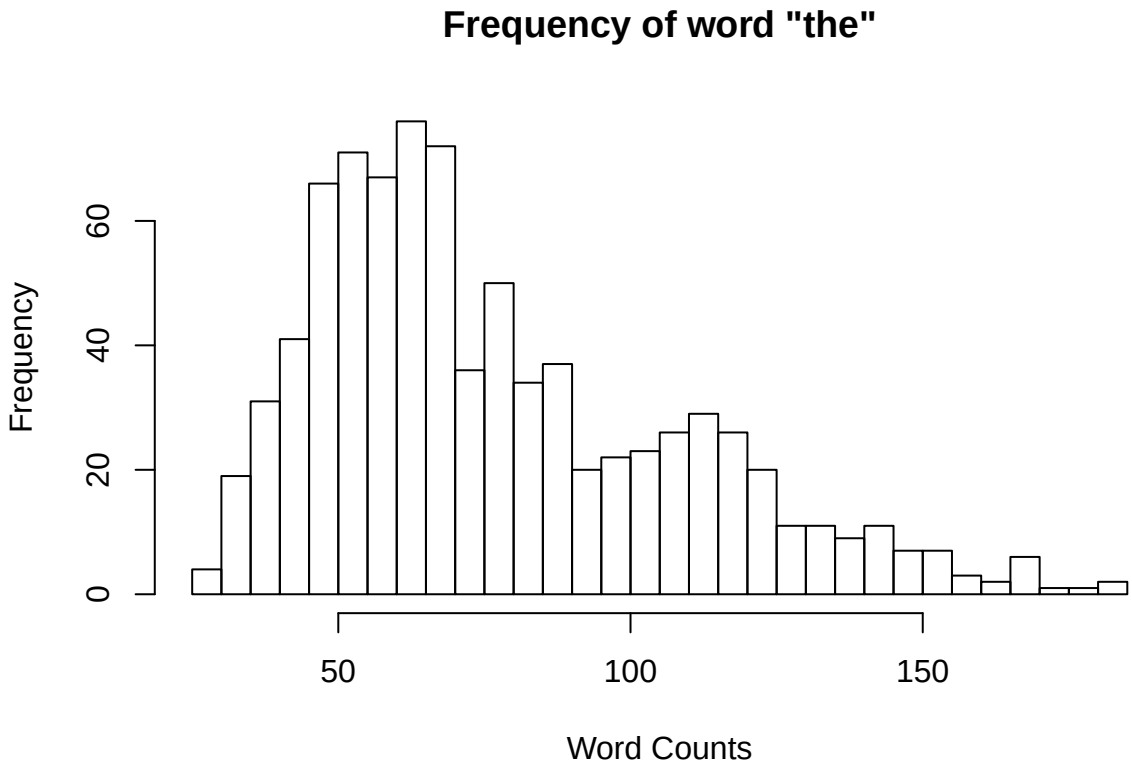
```
##  [1] "a"      "all"    "also"   "an"     "and"    "any"    "are"    "as"
##  [9] "at"     "be"     "been"   "but"    "by"     "can"    "do"     "down"
## [17] "even"   "every"  "for."   "from"   "had"    "has"    "have"   "her"
## [25] "his"    "if."    "in."    "into"   "is"     "it"     "its"    "may"
## [33] "more"   "must"   "my"     "no"     "not"    "now"    "of"     "on"
## [41] "one"    "only"   "or"     "our"    "should" "so"     "some"   "such"
## [49] "than"   "that"   "the"    "their"  "then"   "there"  "things" "this"
## [57] "to"     "up"     "upon"   "was"    "were"   "what"   "when"   "which"
## [65] "who"    "will"   "with"   "would"  "your"   "BookID"
```

```
unique(rownames(author))
```

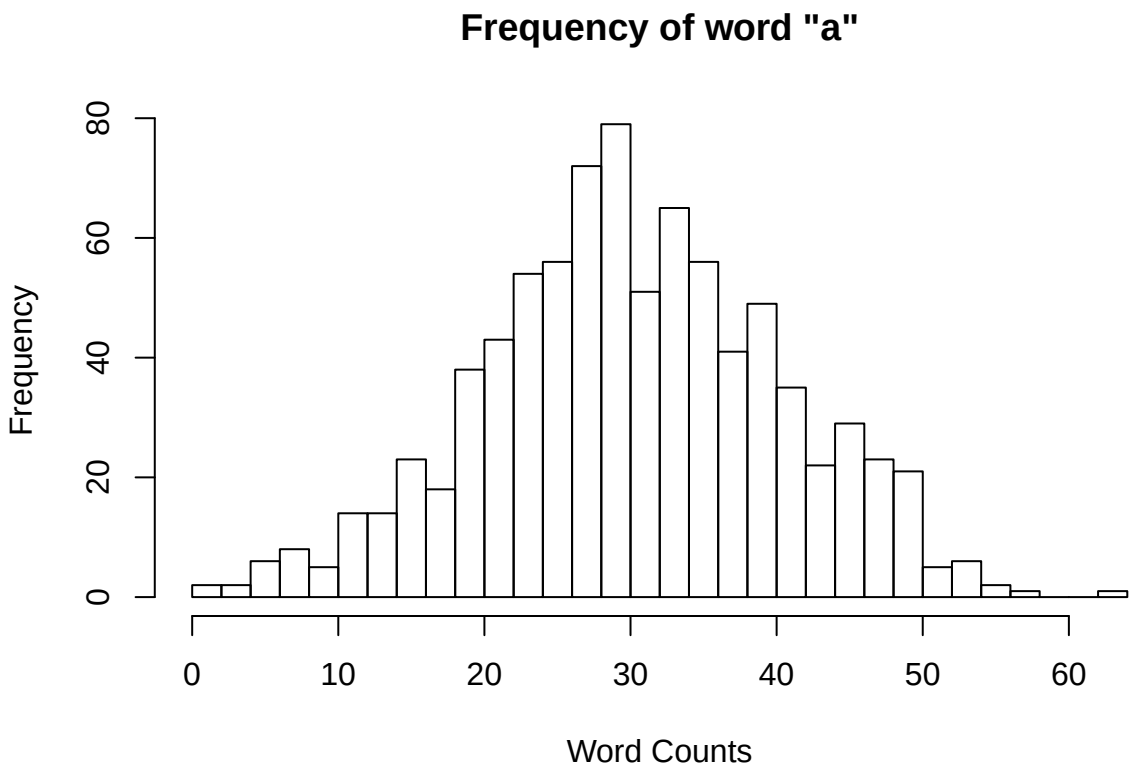
```
## [1] "Austen"      "London"      "Milton"      "Shakespeare"
```

```
TrueAuth = as.factor(rownames(author))
```

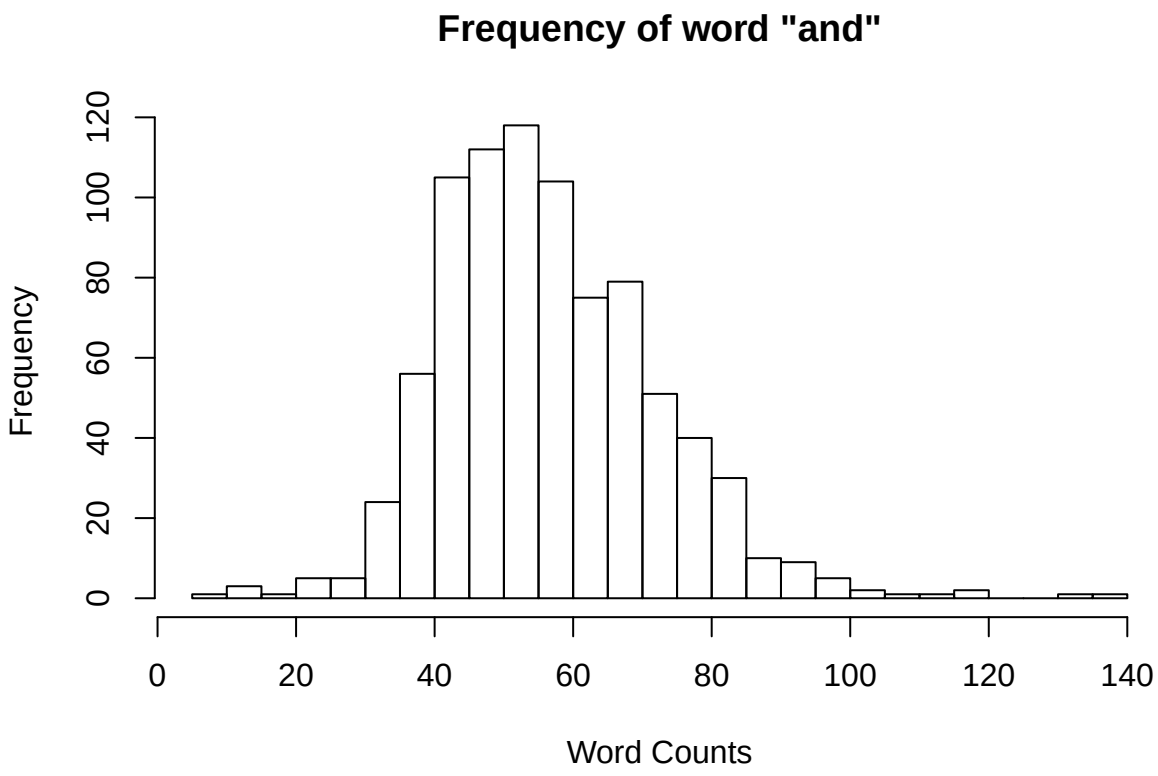
```
hist(author[,colnames(author)=="the"],breaks=25,main="Frequency of word \"the\"",xlab = "Word Counts")
```



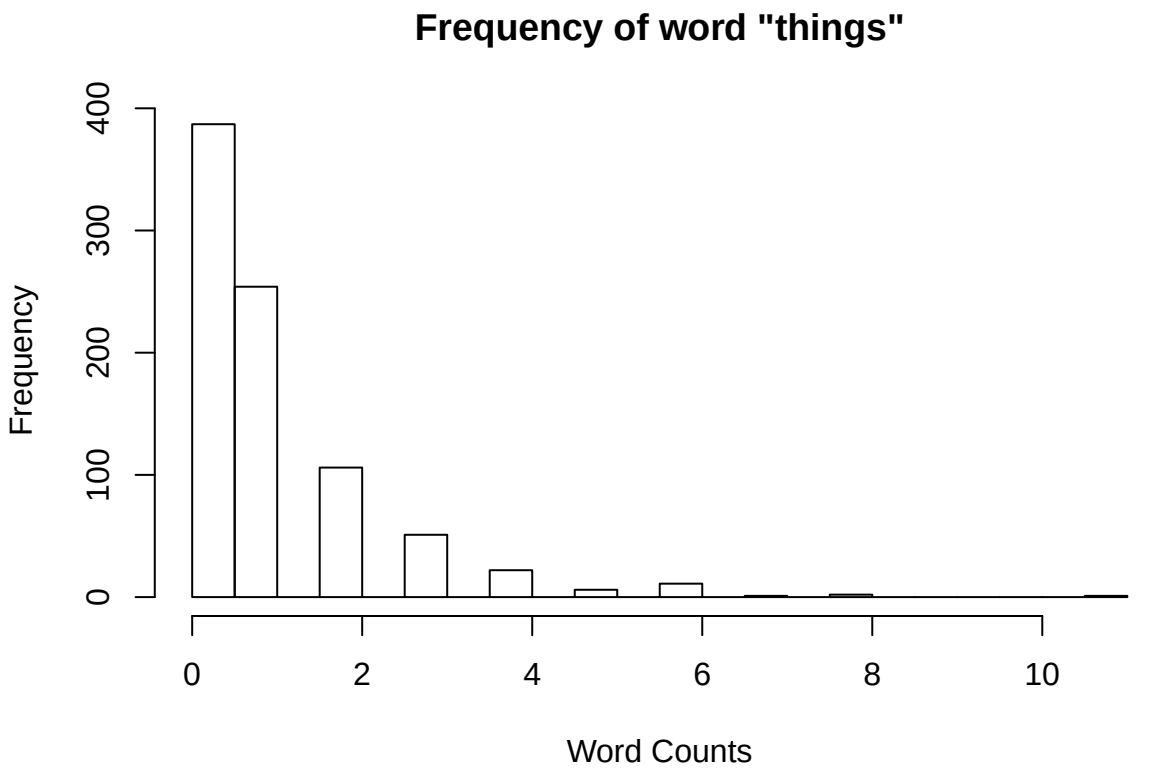

```
hist(author[,colnames(author)=="a"],breaks=25,main="Frequency of word \"a\"",xlab = "Word Counts")
```




```
hist(author[,colnames(author)=="and"],breaks=25,main="Frequency of word \"and\"",xlab = "Word Counts")
```




```
hist(author[,colnames(author)=="things"],breaks=25,main="Frequency of word \"things\"",xlab = "Word Cou
```



Take out bookID

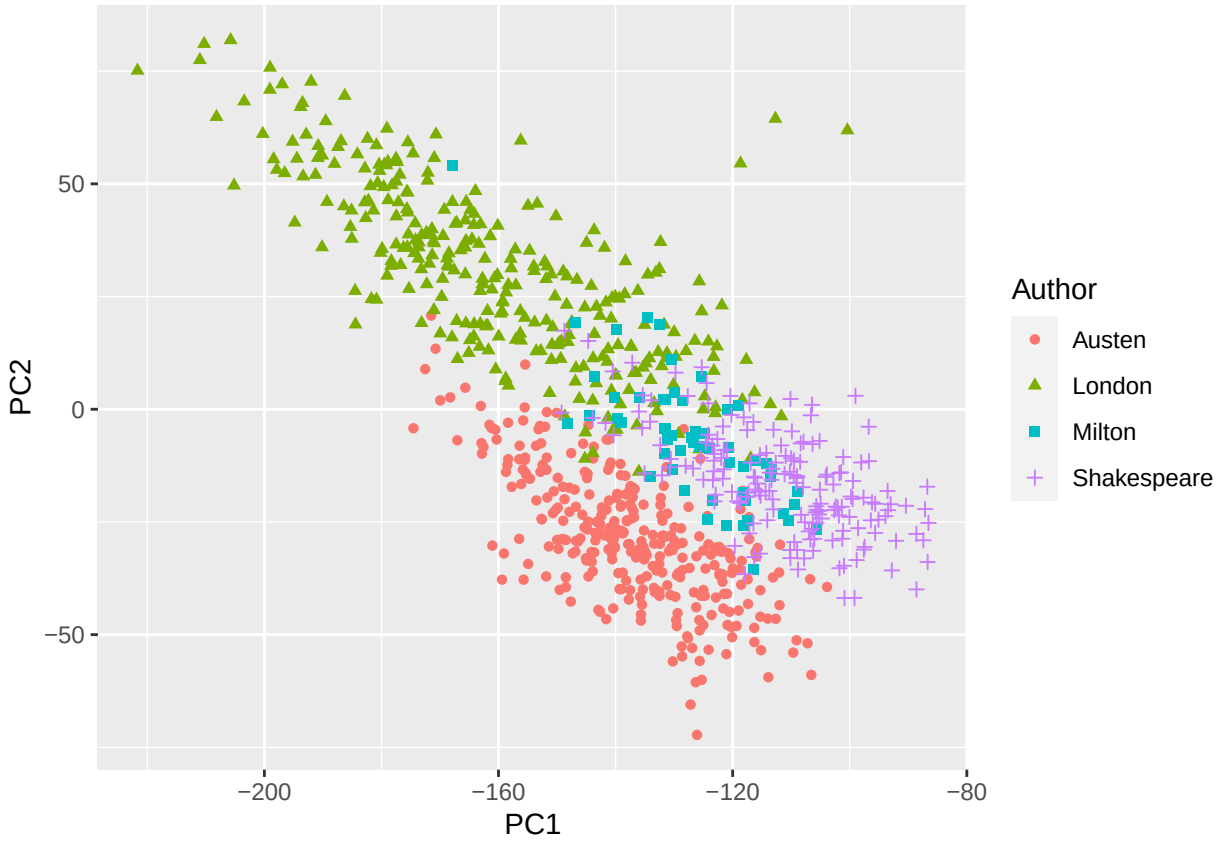
```
AuthorData = author[,1:69]
```

Problem 1 - Visualization

- how to visulaize texts? words? in 2-dimensions

Trying PCA

```
sv = svd(AuthorData)
V = sv$v
Z = AuthorData%*%V
# projected matrix
PCData = data.frame(cbind(Z[,1],Z[,2],rownames(AuthorData)),stringsAsFactors = FALSE)
colnames(PCData) = c("PC1","PC2","Author")
PCData$PC1 = as.numeric(PCData$PC1)
PCData$PC2 = as.numeric(PCData$PC2)
# plot
ggplot(PCData) +
  geom_point(mapping=aes(x = PC1,y= PC2,color = Author,shape= Author))
```



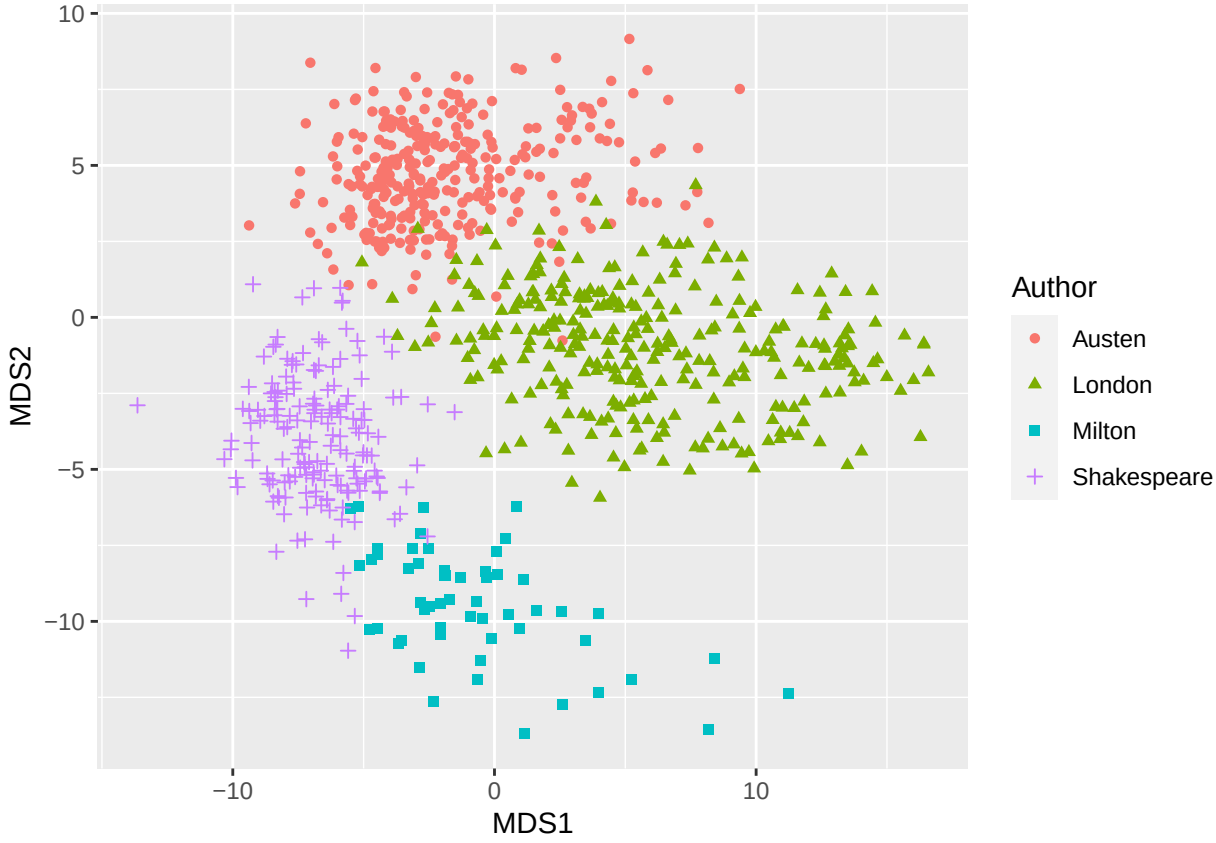
Why doesn't this work well?

Trying MDS (classical)
Can you use MDS to decide which distance is best to understand this data?

Visualizing author texts

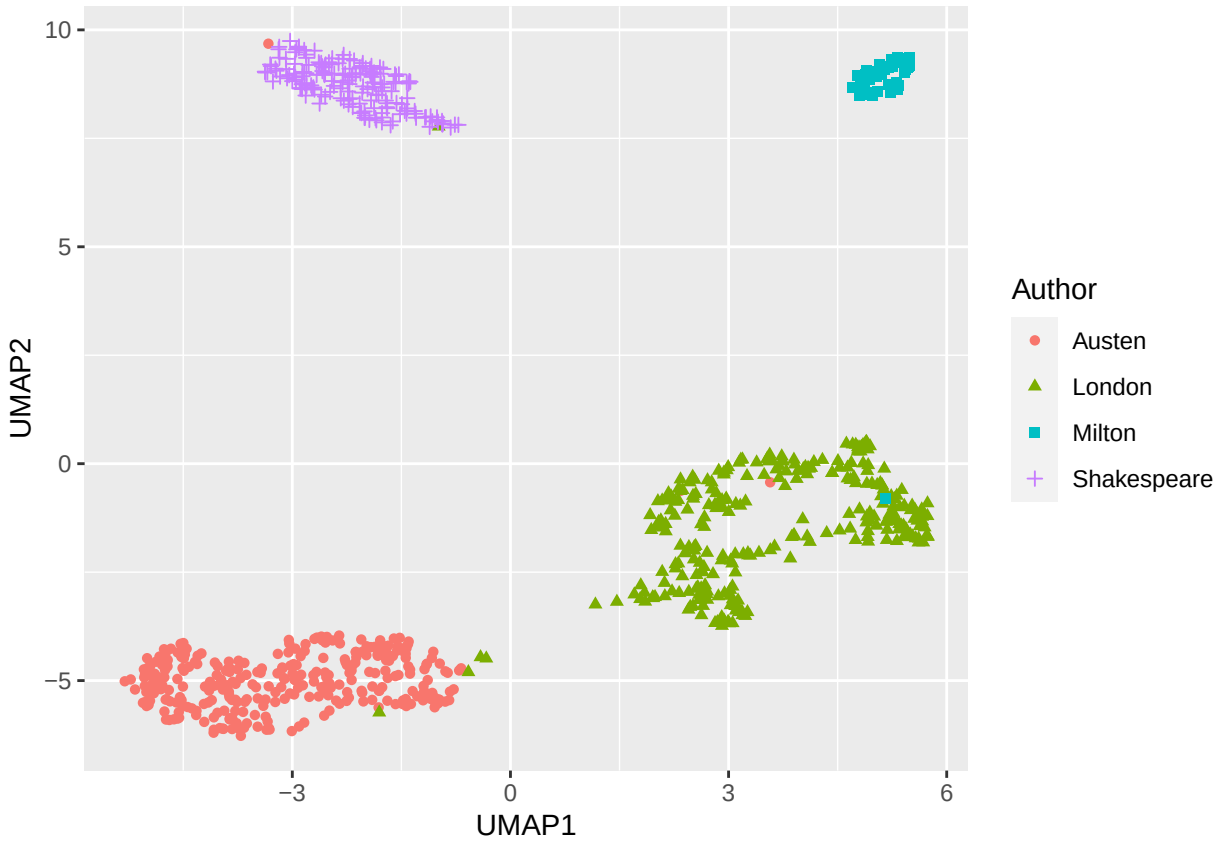
```
Dmat = dist(log(AuthorData+1),method="canberra")
mdsres = cmdscale(Dmat,k=2)
# MDS matrix
MDSData = data.frame(cbind(mdsres[,1],mdsres[,2],rownames(AuthorData)),
                     stringsAsFactors = FALSE)
```

```
colnames(MDSData) = c("MDS1","MDS2","Author")
MDSData$MDS1 = as.numeric(MDSData$MDS1)
MDSData$MDS2 = as.numeric(MDSData$MDS2)
# plot
ggplot(MDSData) +
  geom_point(mapping=aes(x = MDS1,y= MDS2,color = Author,shape= Author))
```



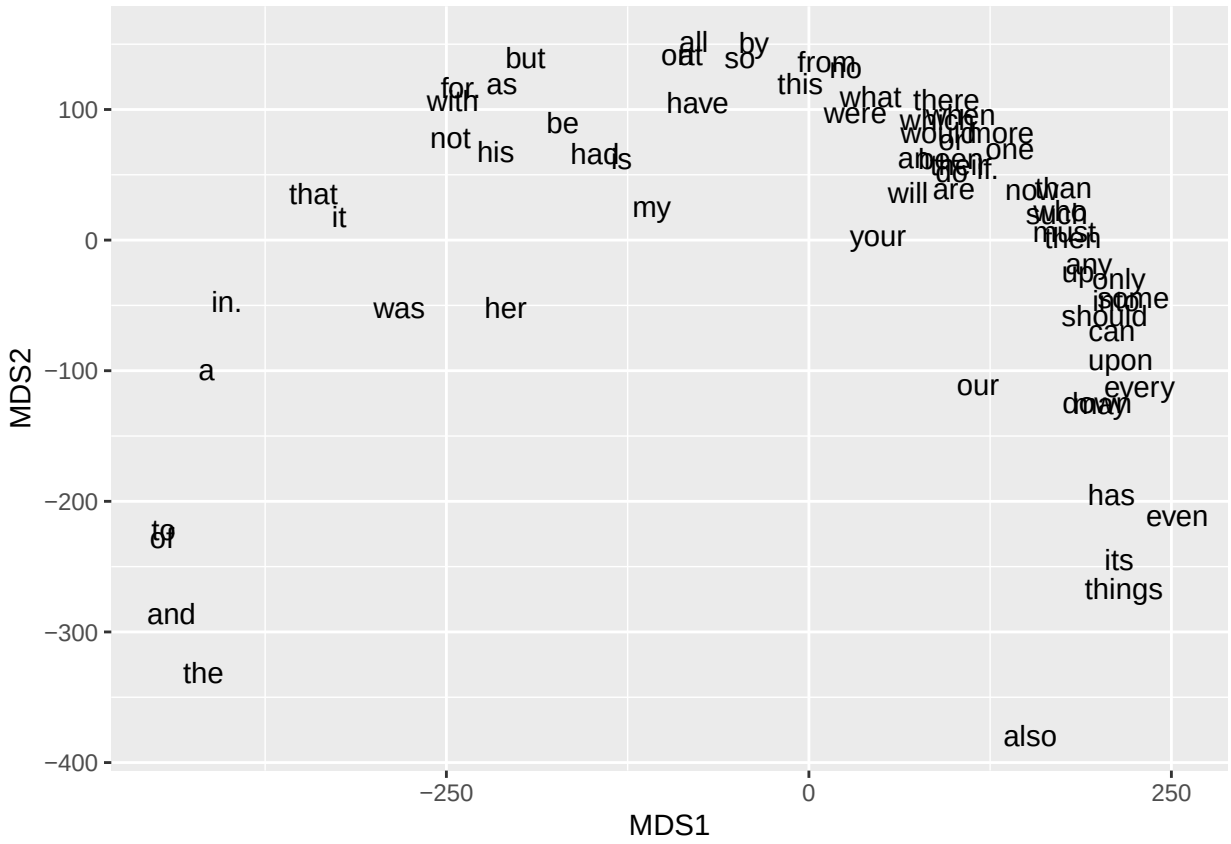
Trying UMAP

```
AuthorUMAP = umap(AuthorData)
# UMAP matrix
UMAPData = data.frame(cbind(AuthorUMAP$layout[,1],AuthorUMAP$layout[,2],
                            rownames(AuthorData)),stringsAsFactors = FALSE)
colnames(UMAPData) = c("UMAP1","UMAP2","Author")
UMAPData$UMAP1 = as.numeric(UMAPData$UMAP1)
UMAPData$UMAP2 = as.numeric(UMAPData$UMAP2)
# plot
ggplot(UMAPData) +
  geom_point(mapping=aes(x = UMAP1,y= UMAP2,color = Author,shape= Author))
```



Visualizing words

```
Dmat = dist(t(AuthorData),method="canberra")
mdsresW = cmdscale(Dmat,k=2)
# MDS matrix for words
MDSDataW = data.frame(cbind(mdsresW[,1],mdsresW[,2],colnames(AuthorData)),
                      stringsAsFactors = FALSE)
colnames(MDSDataW) = c("MDS1","MDS2","Word")
MDSDataW$MDS1 = as.numeric(MDSDataW$MDS1)
MDSDataW$MDS2 = as.numeric(MDSDataW$MDS2)
ggplot(MDSDataW) +
  geom_text(mapping=aes(x = MDS1,y= MDS2,label = Word))
```



Problem 2 - K-means

```
K = 4
km = kmeans(AuthorData,centers=K)
table(km$cluster,TrueAuth)
```

```
##    TrueAuth
##     Austen London Milton Shakespeare
##   1    300     16      0           0
##   2      0      0     54           5
##   3      7    258      1           1
##   4     10     22      0         167
```

Visualization of K-means clustering results via MDS matrix

```
PredData = data.frame(cbind(MDSData[,1:2],km$cluster,rownames(AuthorData)))
colnames(PredData) = c("MDS1","MDS2","PredictedLabel","TrueAuthor")
PredData$PredictedLabel = factor(PredData$PredictedLabel)
ggplot(PredData) +
  geom_point(mapping=aes(x = MDS1,y= MDS2,color = PredictedLabel,shape= TrueAuthor)) +
  ggtitle("Clustering results by K-means with K = 4") +
  theme(plot.title = element_text(hjust = 0.5))
```

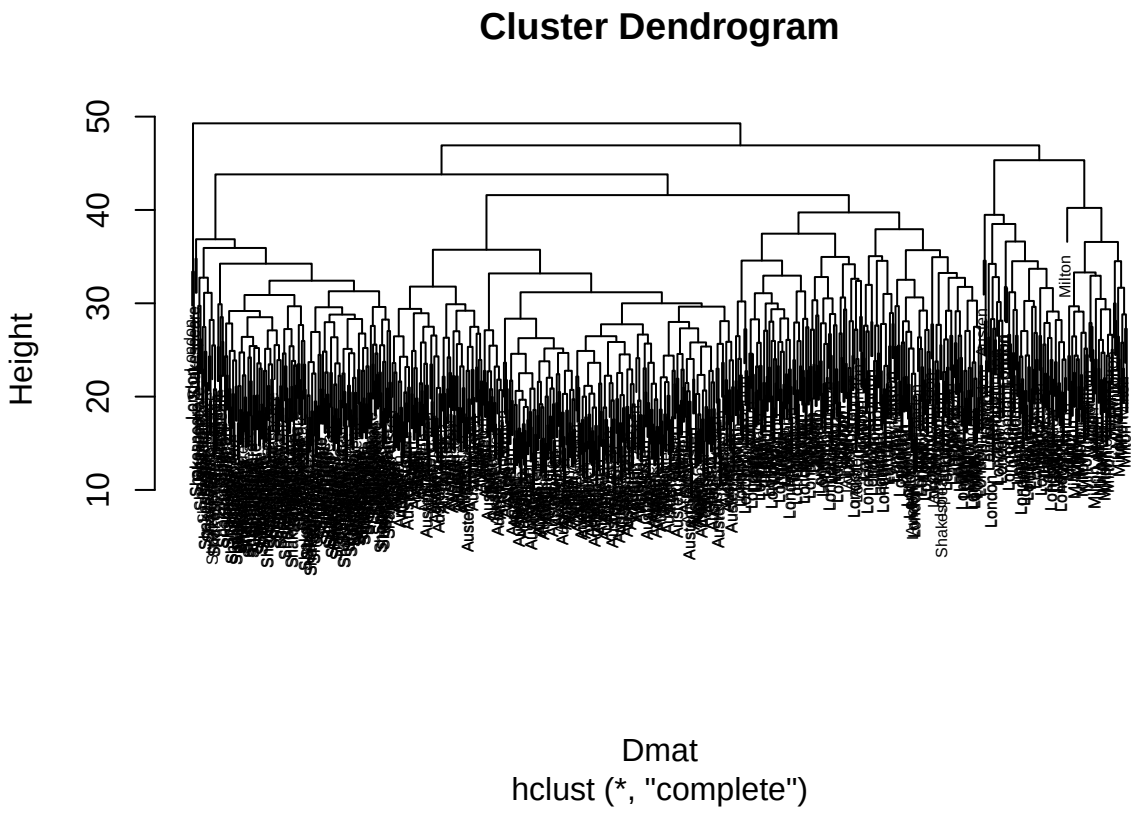
Problem 3 - Hierarchical Clustering

Which distance is appropraite? Why?
canberra distance & complete linkage

```
Dmat = dist(AuthorData,method="canberra")
com.hc = hclust(Dmat,method="complete")
res.com = cutree(com.hc,4)
table(res.com,TrueAuth)
```

```
##         TrueAuth
## res.com Austen London Milton Shakespeare
##       1    316    219      0         173
##       2      1     74      0           0
##       3      0      3      0           0
##       4      0      0     55           0
```

```
plot(com.hc,cex=.5)
```

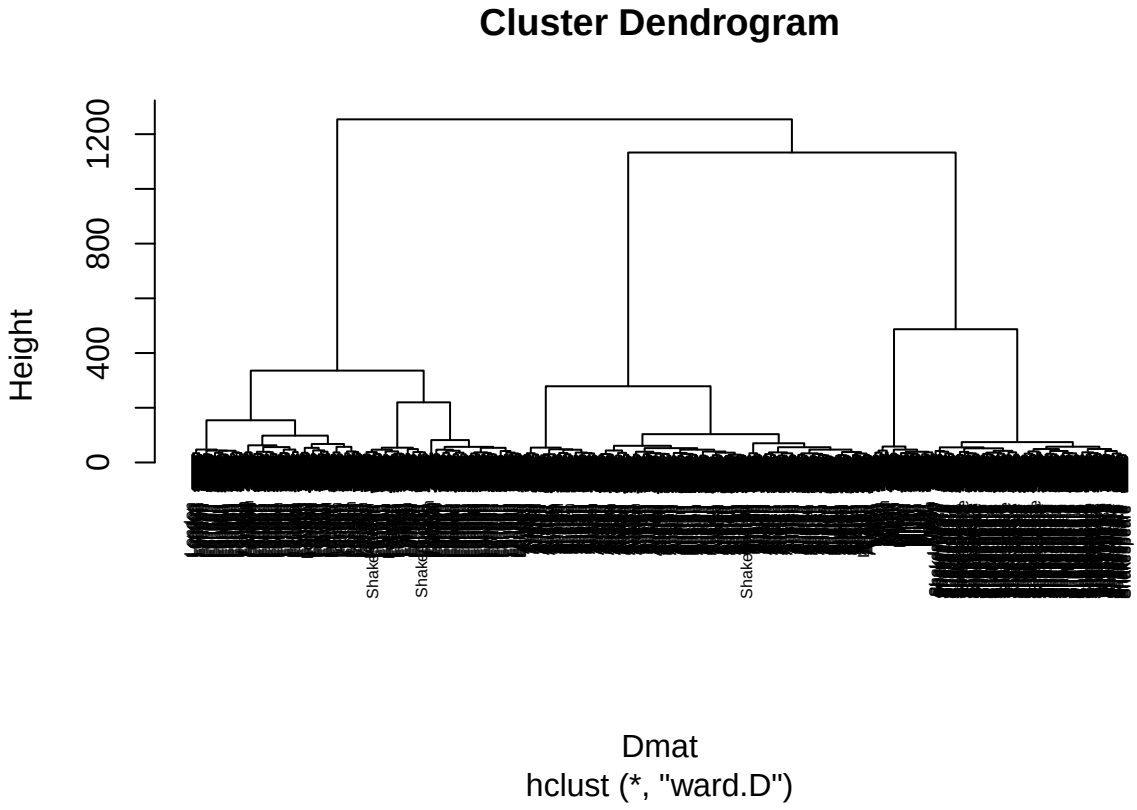


Which linkage is best? Why?
canberra distance & ward.D linkage

```
Dmat = dist(AuthorData,method="canberra")
ward.hc = hclust(Dmat,method="ward.D")
res.ward = cutree(ward.hc,4)
table(res.ward,TrueAuth)
```

```
##          TrueAuth
## res.ward Austen London Milton Shakespeare
##        1    312      1      0           1
##        2      1      3      0         170
##        3      4    292      0           2
##        4      0      0     55           0
```

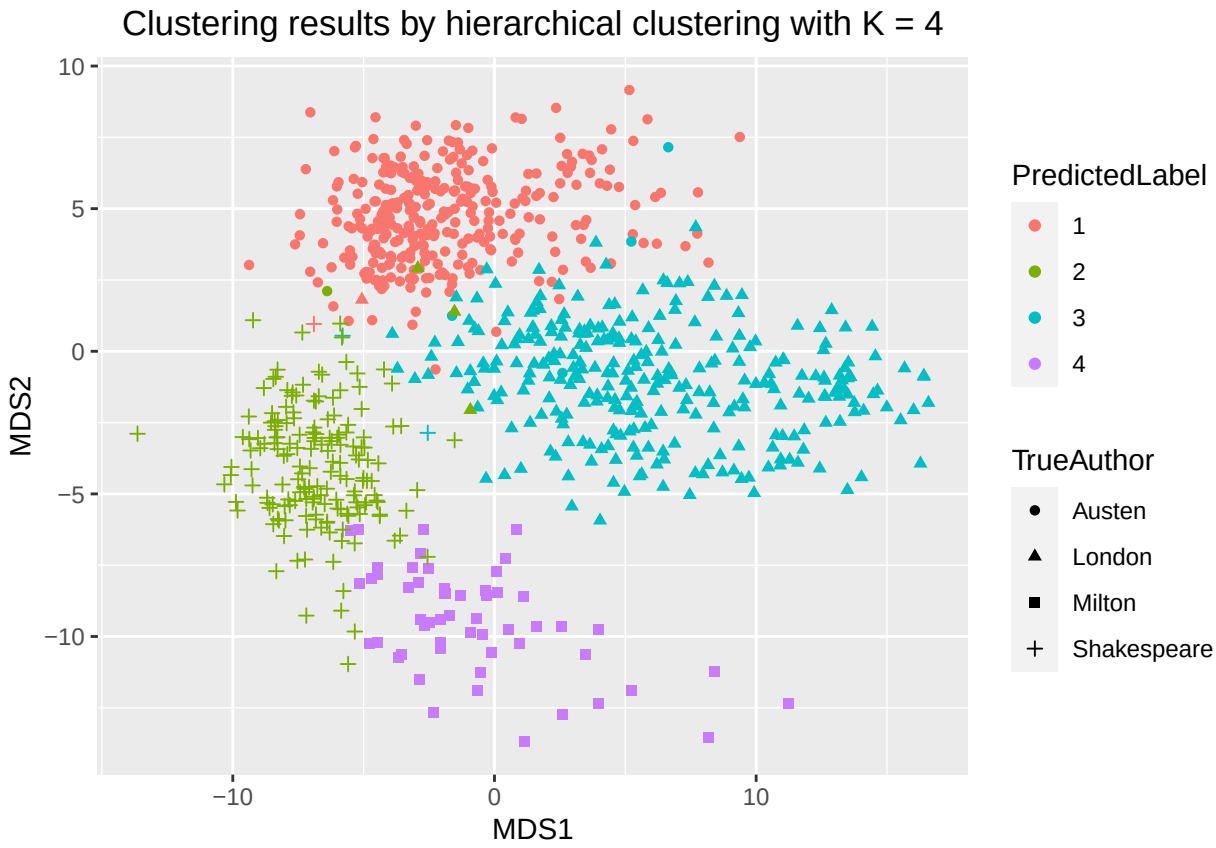
```
plot(ward.hc,cex=.5)
```



We can see that canberra distance and ward.D linkage give excellent clustering results.

Do any preform terribly? Why?
Visualizing hierarchical clustering results using MDS.

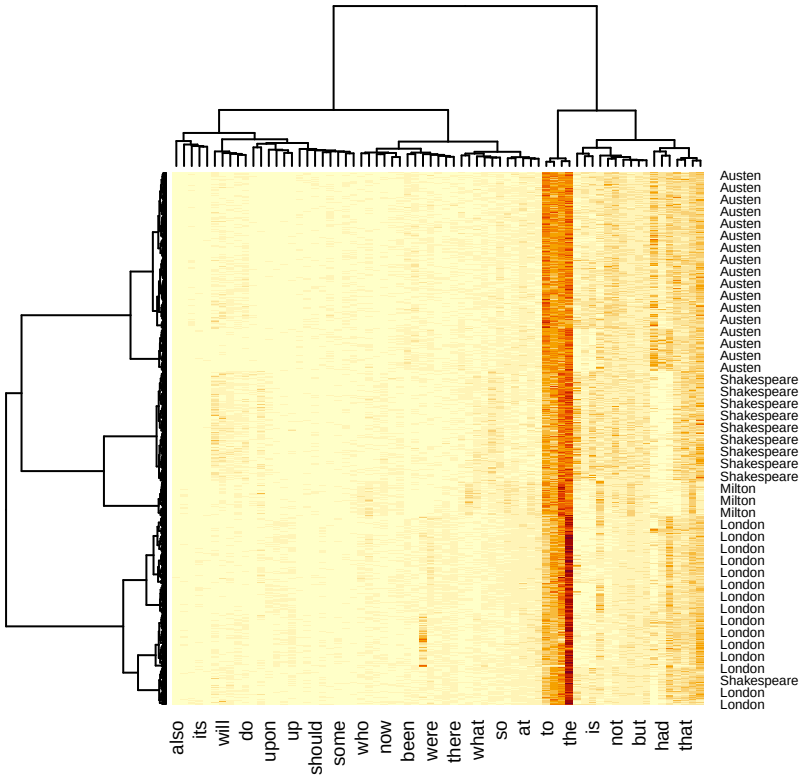
```
PredData = data.frame(cbind(MDSData[,1:2],res.ward,rownames(AuthorData)))
colnames(PredData) = c("MDS1","MDS2","PredictedLabel","TrueAuthor")
PredData$PredictedLabel = factor(PredData$PredictedLabel)
ggplot(PredData) +
  geom_point(mapping=aes(x = MDS1,y= MDS2,color = PredictedLabel,shape= TrueAuthor)) +
  ggtitle("Clustering results by hierarchical clustering with K = 4") +
  theme(plot.title = element_text(hjust = 0.5))
```



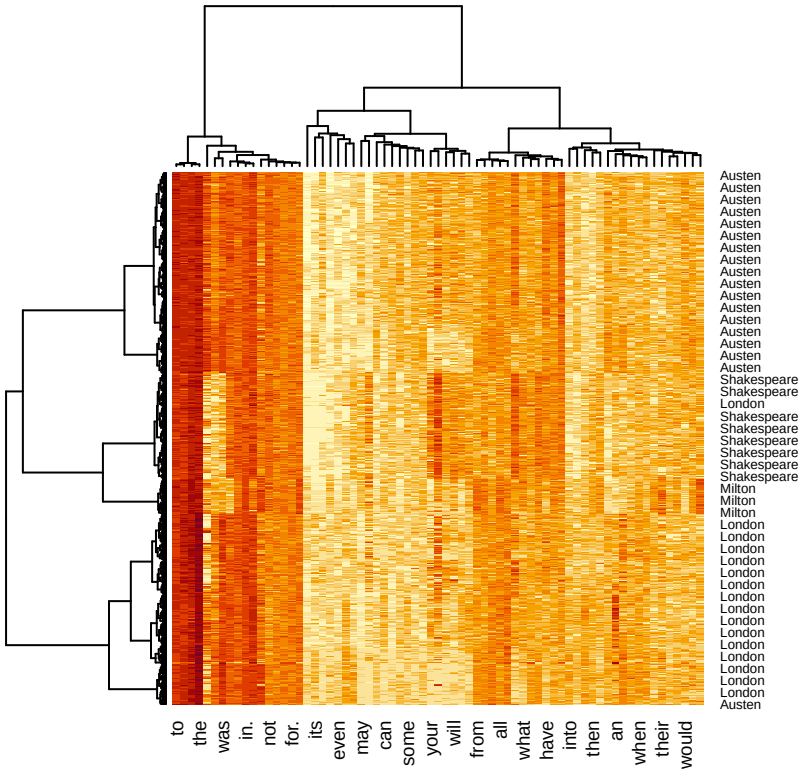
Problem 4 - Biclustering

Cluster heatmap

```
heatmap(AuthorData,
        distfun=function(x)dist(x,method="canberra"),
        hclustfun=function(x)hclust(x,method="ward.D"))
```




```
heatmap(log(AuthorData+1),
        distfun=function(x)dist(x,method="canberra"),
        hclustfun=function(x)hclust(x,method="ward.D"))
```



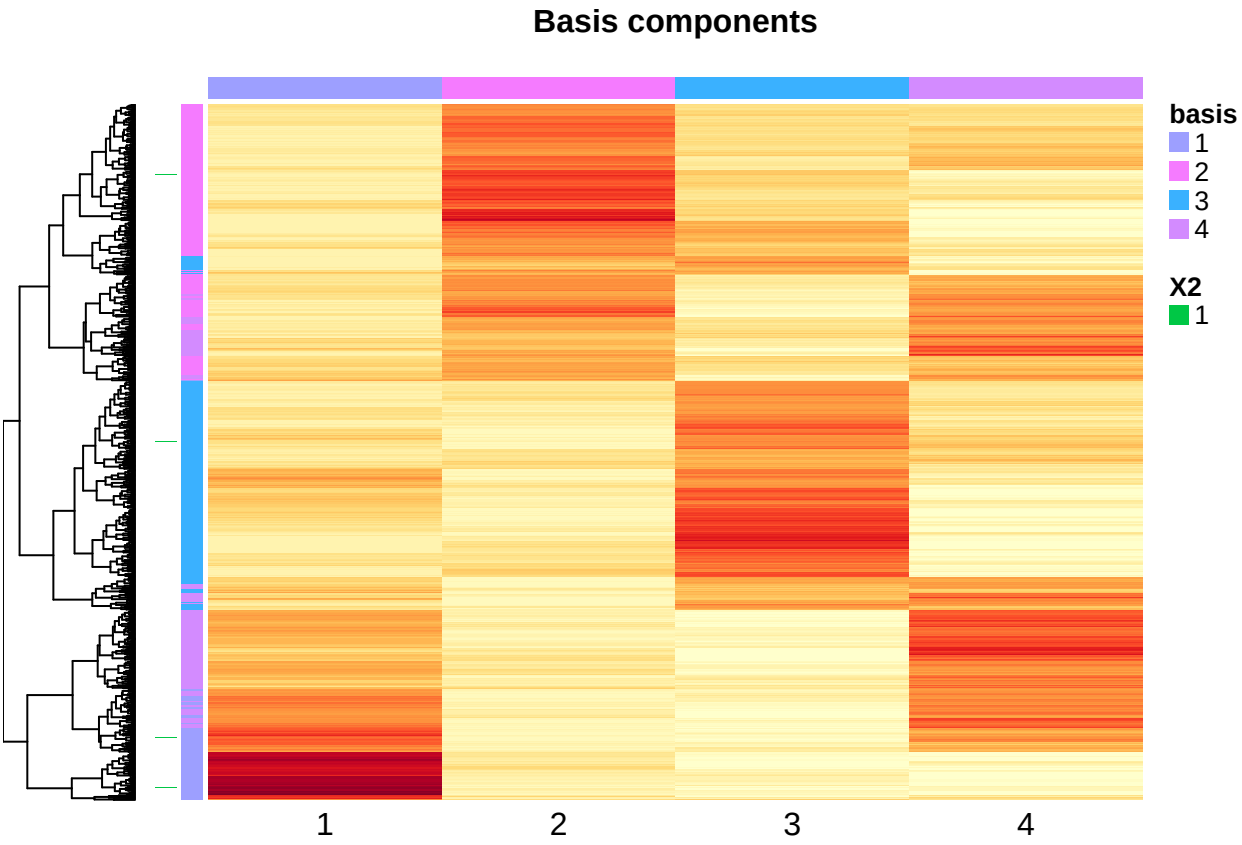
Problem 5 - NMF

```
K = 4
nmffit = nmf(AuthorData,rank=K)
W = basis(nmffit)
H = coef(nmffit)
```

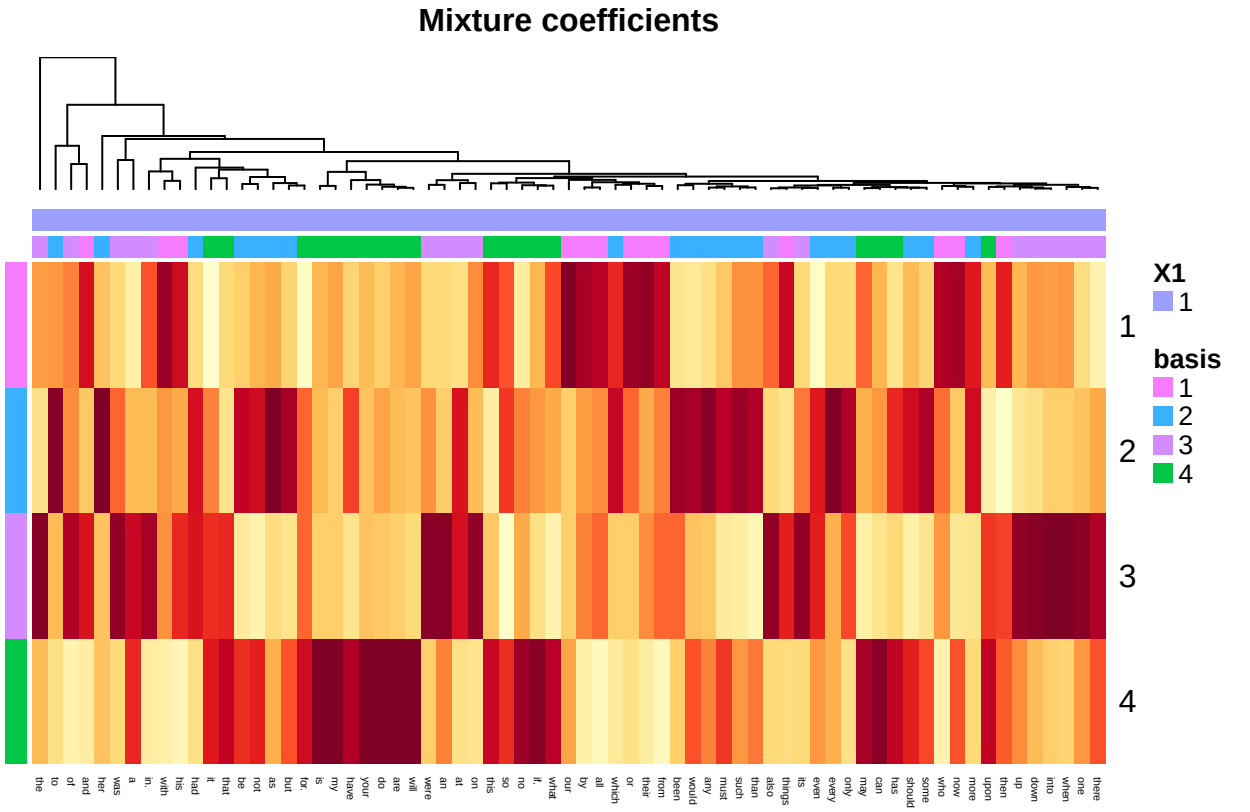
```
cmap = apply(W,1,which.max)
table(cmap,TrueAuth)
```

```
##     TrueAuth
## cmap Austen London Milton Shakespeare
##    1      1      1     55          51
##    2    262      1      0           0
##    3      4    274      0           0
##    4     50     20      0         122
```

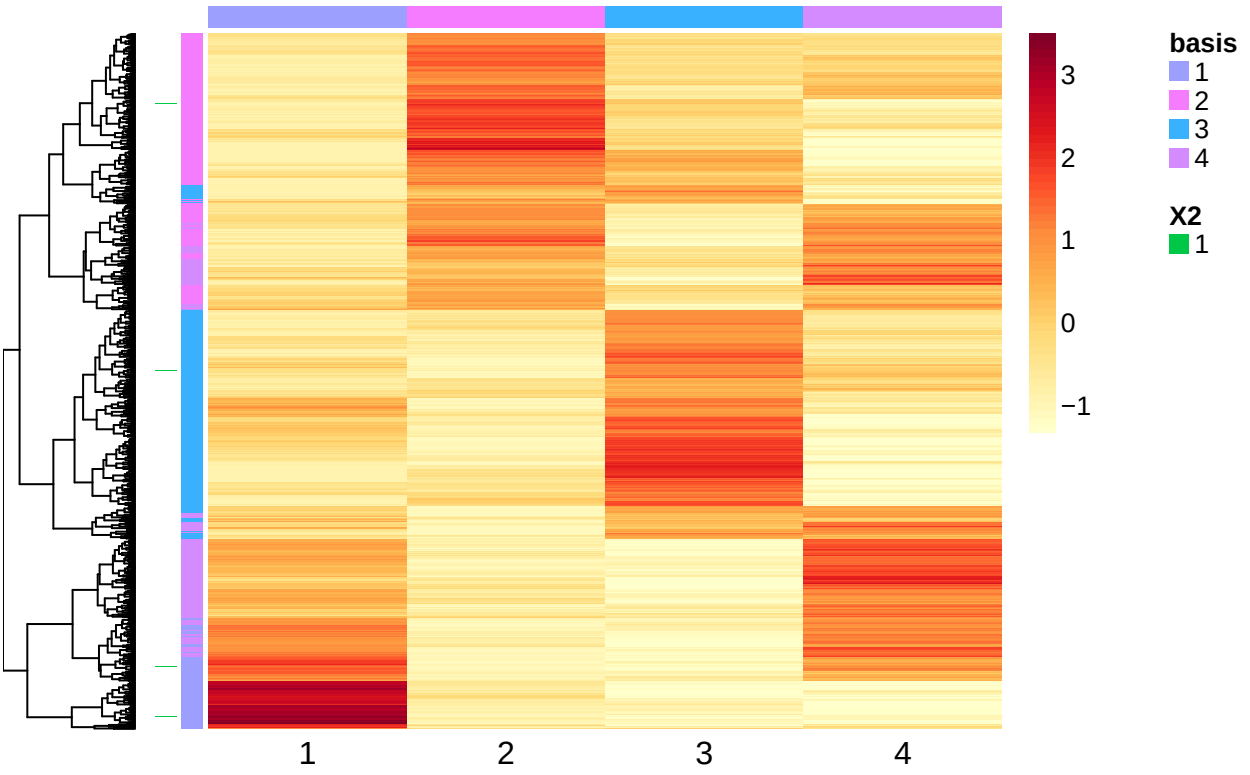
```
basismap(nmffit,annRow=rownames(AuthorData),scale="col",legend=FALSE)
```



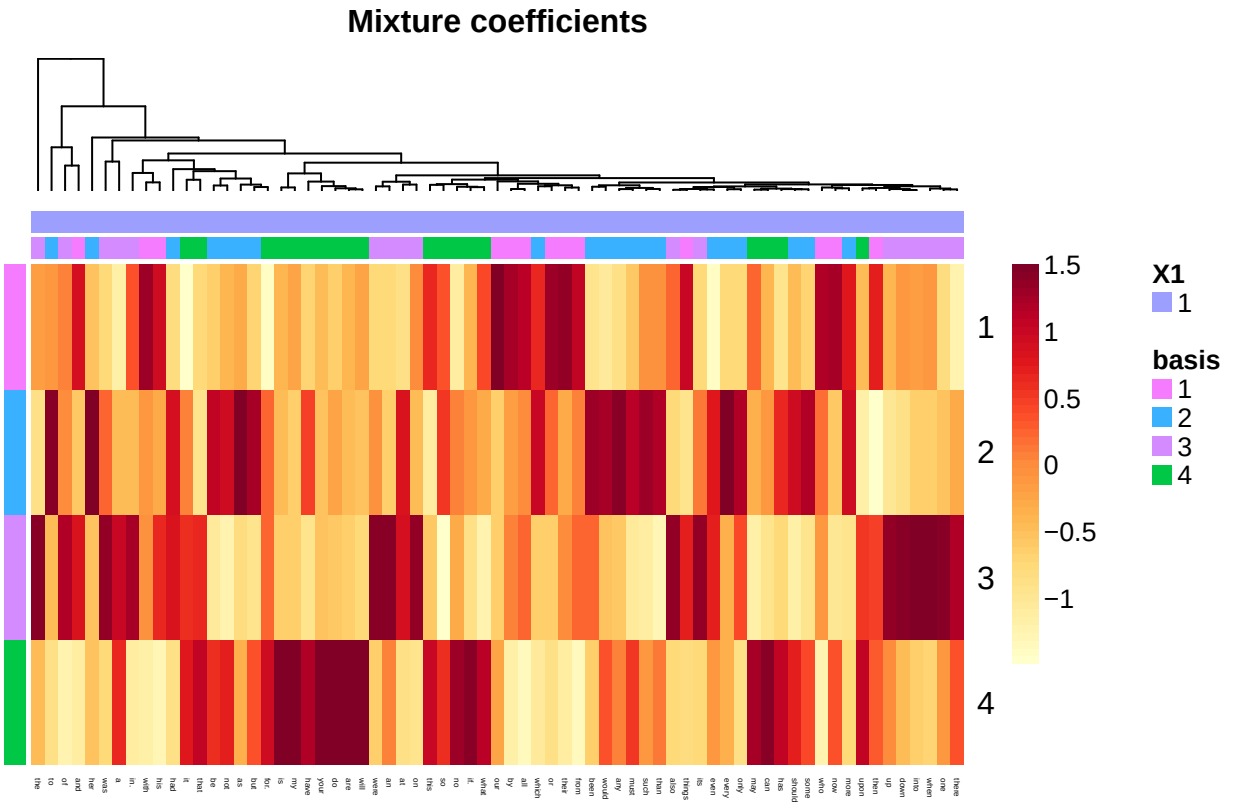

```
coefmap(nmffit,annCol=colnames(AuthorData),scale="col",legend=FALSE)
```




```
basismap(nmffit,annRow=rownames(AuthorData),scale="col",legend=T)
```



```
coefmap(nmffit,annCol=colnames(AuthorData),scale="col",legend=T)
```



Which words are most important for distinguishing authors?